The Safety/Efficiency Synergy: Queuing Analysis and Exposure to Infectious Diseases

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Introduction:

Question: How do queueing controls in pandemic-modified operational systems relate to exposure rate and potential for disease transmission?

- Simulation using stochastic infection rates and sojourn time periods model exposure rate with given parameters.
- The measured metric resembles common R_0 nomenclature – the number of new transmissions that may result over a collection of arrivals and could be further deduced to estimate the transmission rate per new arrival into the system.
- Sherwin Doroudi (Asst. Professor in the Department of Industrial and Systems Engineering), Kang Kang (Ph.D, Industrial and Systems Engineering), and Alexander Wickeham (Ph.D, Industrial and Systems Engineering) are developing a model that synthesize customer behavior models found in popular queuing theory.

Hypothesis: Reduction of staffing levels and capacity limitations in a service operations environment may lead to extended customer wait time and increased exposure risk for COVID-19 transmission through air particle.

Objectives

- Simulate the effect of system parameter manipulations on a constructed service environment from the perspective of disease transmissibility.
- Discuss how human-crafted controls such as capacity limitations, use of facemasks, and social distancing policies can affect the concentration and transmission rate of infectious diseases similar to COVID-19.
- Construct the foundations of a simulator for the developed model (Doroudi, Wickeham, and Kang, 2021.) that can be enhanced with new corresponding model additions.
- Gain further insights into the practical use of simulation to explain scientific and mathematical phenomena.

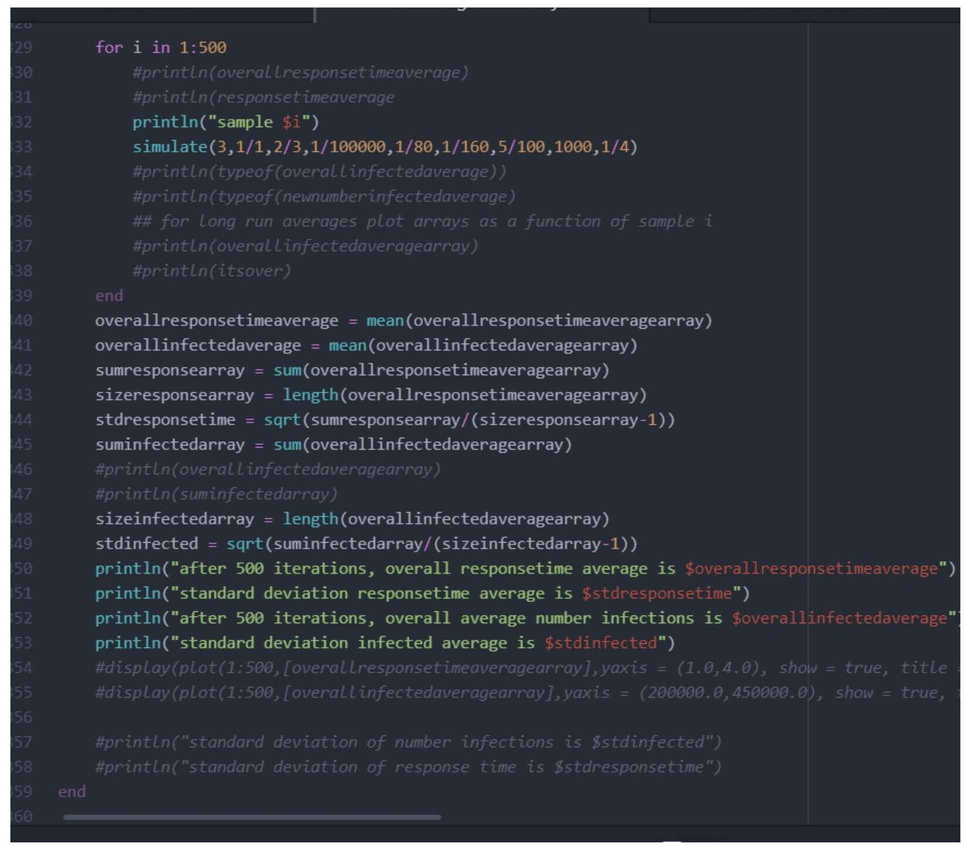
Materials and Methods

1. *Baseline Model:* M/M/1 simulator with the assumptions from Poisson arrivals and exponential service times.
2. Five initial exponential variables were created in a tailorable format: *arrival rate, service rate, infection threshold, emission rate, decay rate*
3. To mimic capacity limitations (**25%, 50%, 75%, etc**.), the emission parameter was varied as such.
4. The parameter *p*, representing the probability of a customer entering the system infected was also varied in addition to the number of servers *C*.
5. If the cumulative exposure an arrival encounters is greater than their threshold for infection, randomly assigned in this simulation, they experience a transmission and become infected with the associated disease.
6. Once infected, the customer contributes to the systematic particle count until they depart with the potential to infect future arrivals
7. The simulator function that tested 1,000,000 arrivals with given parameters to find average sojourn times and number of newly infected cases.
8. This function was embedded inside another that ran this simulation 500 rounds to get long term results per million arrivals.

Figure 1: Simulation Parameters

$\lambda=1/1$
$\mu=2/3$
$\beta=1/80$
$\Gamma=1/160$
N = 1,000,000
f = 1/4

Figure 2: Coding Environment Structure in Julia



Results

Tested Parameters:

- four different amounts of servers (C) - 2,3,4,5
- five different initial exposure probabilities (p) - 0.02 – 0.06
- four different emission parameters – 0.125, 0.25,0.5,0.75.

Results:

- A proportional trend in the number of infections steadily increasing as the initial exposure probability increased: starting from ~5.4 and ending at ~16.5 per million arrivals.
- As the number of servers was increased, the number infections decreased along with the average sojourn time. For 2 servers, a sojourn time of 1.853 was reported along with 46.02 infections. At 5 servers, the sojourn time was 1.229 and number of infections was 10.12 infections.
- As the rate of emission increased, the number of infections also increased,. At an emission rate of 1/8, the number of infections was 9.12 per million and at 3/4, it was 33.48 per million.

Figure 2 shows a specific example of the long term converging average number of new infections and response time at a C = 3, p = 0.05, and emission rate of 100%.

Interpretation: Limitations on exposure rate via capacity restrictions or social distancing measures do influence number of transmissions in this simulation model. Longer response times resulting from fewer staff members or process inefficiency can affect the potential for customer infections within a service environment.

Table 1: Summary of Experimentation Results

N = 1000000, 500 iterations of the function	Average Number Infections (per million)	Standard Deviation of Infections	Response Time (undisclosed units)	Standard deviation of response time
P = 0.02 (C = 3)	5.34	2.3	1.736	1.319
P = 0.03 (C = 3)	8.35	2.89	1.736	1.319
P = 0.04 (C = 3)	11.32	3.37	1.736	1.319
P = 0.05 (C = 3)	14.36	3.81	1.737	1.319
P = 0.06 (C = 3)	16.598	4.07	1.737	1.319
C				
3				
2 (P =0.05)	46.02	6.70	3.42	1.853
4 (P = 0.05)	10.99	3.33	1.544	1.244
5 (P = 0.05)	10.12	3.34	1.508	1.229
Now adding f parameter for emission rate (C = 3)				
1/8	9.12	3.02	1.736	1.319
1/2	25.91	5.03	1.736	1.319
3/4	33.48	5.79	1.736	1.319

Figure 3: Long Term Response Time Average (C = 3, p = 0.05)

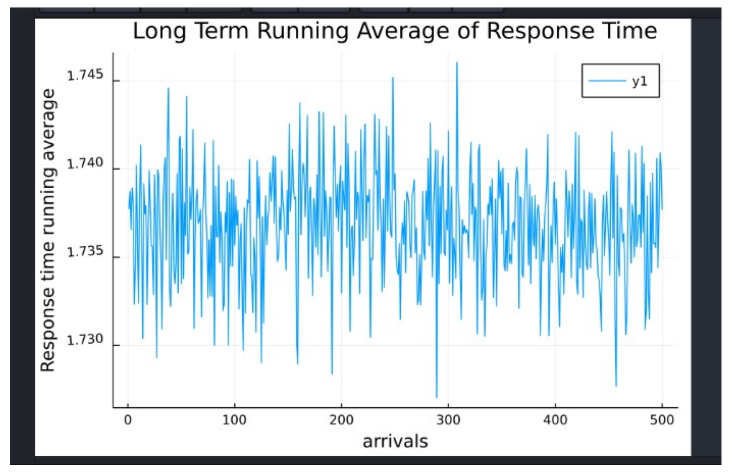
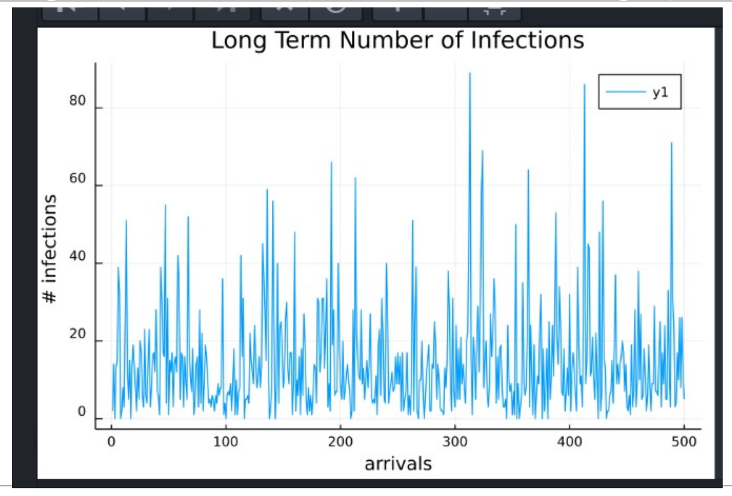


Figure 4: Long Term Number New Infections Average (C = 3, p = 0.05)



Conclusion

Opportunities for Future Study:

- How would the infection of a staff member effect disease transmission within this system?
- Craft testing scenarios with increased accuracy and realistic representation ,knowing that real-time infection probabilities are generally low but increase exponentially with the number of particles present.
- Simulate situations of high utilization (50-70%) to increase the possibility of substantial queuing systems to form and potential for significant numbers of infections arise
- Adding an additional parameter to represent the reproduction of particles on an exponential scale. For COVID -19, scientists estimate the reproductive rate to be 2 – 3 per unit time for infected personnel.. Customer Prioritization: high risk customers are aimed to be served with a smaller sojourn time with the purpose of decreasing systemwide transmission rate.

Societal Impacts:

- The formation of ideal queuing arranges from a safety and efficiency standpoint (e.g.: snake queue, omni-channel queueing).
- Similar optimization techniques can be applied from the lens of social distancing and capacity control in system queuing design.
- Continuing research and justification behind commonly known combat techniques to the spread of disease: social distancing with given parameters and the use of a mask knowing rates and optimal scenarios for disease transmission.

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